Identification of academic peer effects in college: Does data aggregation matter?

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ABSTRACT

This study exploited random roommate assignments in a small Chinese college to estimate the causal effects of roommates' scores on the national College Entrance Test (CET) on first-year students' Grade Point Average (GPA). Analyzing data on an entire cohort of enrolled students, we found that the level of aggregation, for both the peer-ability measure and one's own academic-outcome measure, matters for the identification of academic peer effects. Specifically, while roommates' average CET score has a barely significant impact, the highest-scoring roommate's CET score has a strong positive impact. Peer effects are also larger for one's GPA for required courses than that of elective courses. Finally, peer effects in both types of courses decline over time while the effects of one's own CET score increase over time, suggesting that students in this college tend to substitute their own ability for peer ability as they become more academically independent.

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1. INTRODUCTION

Peer effects have been a central topic in educational research [1]–[4]. Concerning higher education, how peers' academic ability affects college students' academic performance has important implications for course design and student management in colleges and universities [5]–[7], especially in countries whose higher education system is undergoing rapid reforms and development [8]. For example, to improve students' academic outcomes, should college administrators adopt a "tracking" strategy, grouping students with similar levels of academic ability in classes, study groups, and even dorm rooms? Or, should they adopt a "mixing" strategy and encourage students to join others with different levels of ability? The answers to these questions hinge on whether significant academic peer effects exist among college students, i.e., whether students would learn more (less) when grouped with academically stronger (weaker) peers. Tracking is preferred in the absence of positive peer effects because, in that case, schools can tailor their educational resources to fit each group's ability level. In contrast, the mixing strategy may be considered desirable in the presence of peer effects, provided that the gains enjoyed by academically weaker students substantially outweigh the losses endured by academically stronger ones.

However, finding credible evidence of academic peer effects is usually difficult in observational studies [9]–[11]. A strongly positive association between one's own and peers' academic outcomes observed in the data may not necessarily imply the existence of peer effects. Students' self-selection into peer groups with similar characteristics, and unobserved confounders that simultaneously affect individual students and their peers, may induce a positive association between their academic outcomes even if there exist no real peer effects [2], [9]–[11].

The identification strategy devised by Sacerdote [12], which exploits random roommate assignments in certain colleges, offers an effective means to address the aforementioned problems. A series of subsequent studies [13]–[23] adopted this strategy. They further circumvented reverse causality from individual students' performance on their peers' performance by employing pre-college measures of peer ability (e.g., SAT scores or high school ranking) as the key explanatory variable. Yet, somewhat puzzlingly, despite the conceptual soundness of this identification strategy, only a few studies adopting this strategy found statistically significant peer effects among college students [11].

More importantly, in the handful of studies that did find significant peer effects using this strategy, the peer effects they identified appear to be quite heterogeneous across subjects and subgroups of students. Some studies found peer effects to be major-specific. For example, at an Italian university, Brunello *et al*. [14] found significant peer effects among students majoring in physics and computer science but not those majoring in social sciences or humanities. Some other studies found peer effects to be course-specific within majors. For example, at the United States Air Force Academy, Carrell *et al*. [15] found significant peer effects in mathematics and science but found virtually no peer effects in physical education and foreign language. Still other studies found peer effects that differ across gender groups [16], [17] and ability levels [18], [19]. Although discovered in different settings, these findings suggest that academic peer effects may work through various channels.

Yet, can these potentially different channels be understood within a unified framework that may guide spotting potential peer effects? This paper attempts to provide an answer, at least a partial one, to this question. We argue that a simple demand-and-supply framework goes a long way. Intuitively, in the "market" for peer interaction, both the demand side (who *needs* help?) and the supply side (who *can* help?) affect the magnitude of peer effects realized in equilibrium. First of all, students' demand and supply may take various forms. For example, by frequently sitting next to each other during lectures or studying together, students may raise each other's motivation to study hard [24]. Academically weaker students may also understand course materials better if they regularly borrow notes from their abler classmates [6], [7]. Naturally, these different forms of peer interaction are likely to generate peer effects of different sizes. Secondly, the size and thickness of the "market" for peer interaction may vary with context: the frequency and intensity of a given form of peer interaction may depend on the course contents covered and the level of difficulty in digesting these contents. It follows that the magnitude of peer effects may also differ across majors (e.g., "hard" sciences versus humanities), course types (e.g., math-intensive versus math-free), and individual characteristics (e.g., low- versus high-ability). Yet, many of these channels may be masked in aggregate outcome measures (e.g., accumulative Grade Point Average) and peer-ability measures (e.g., roommates' average pre-college test score). The simple demand-and-supply framework discussed implies that the level of data aggregation matters for the identification of academic peer effects.

The present study exploited random roommate assignments (conditional on students' major) in a small college in China's Shandong province and provided quasi-experimental evidence that supports the previous argument. Using data on the entire cohort of 290 first-year students enrolled in the fall, we estimate the causal effect of roommates' scores on the National College Entrance Exam (CET) on individual students' Grade Point Average (GPA). Considerable efforts are devoted to investigating how different roommates' CET scores and individual students' different GPA measures, e.g., those computed separately for different types of courses (required versus elective) and semesters (fall versus spring), may affect the estimates of academic peer effects.

2. RESEARCH METHOD

2.1. Study environment

The data analyzed in this study were collected from a small public four-year college, the Yantai Institute, located in a vibrant coastal city (Yantai) in Shandong province of China. The Institute was founded in 1993 with a mission to serve local communities by training its students to meet local demands for skilled labor. Currently, it offers four majors, namely, Aquaculture, Facility Agriculture, Marketing, and Public Administration, admitting about 300 students (all from Shandong Province, China) each academic year.

Despite its relatively small size, the student population of this Institute has several attractive features that can help reveal potential academic peer effects. First, unlike most colleges investigated in previous studies, the Yantai Institute is not highly selective. Thus, students enrolled in this Institute are more likely to benefit from peer interaction than their counterparts from highly selective colleges previously studied, such as Dartmouth College [12] and Williams College [13] in the United States. Second, the small size of the Institute provides a fairly "controlled" and homogenous learning environment, in which peer influence may explain a relatively large proportion of the variation in one's academic outcomes. In particular, compared with students attending larger colleges, the relatively limited pool of potential "friends" for students attending the Institute suggests that their roommates, who are also their classmates in many classes, may serve as their most influential academic peers. Finally, each student attending this Institute has multiple roommates, allowing us to examine the relative effects of different roommates' academic abilities.

2.2. Student recruitment and roommate assignments

As with most tertiary institutions in China, the Yantai Institute recruits students through the national College Entrance Test (CET) system [25]–[27]. Similar to students admitted elsewhere in China [17], [21], [25]–[27], students recruited by this Institute came from two academic tracks, i.e., the General Science track (*li-ke*) and the Liberal Arts track (*wen-ke*). High school seniors in both tracks took five tests, i.e., separate tests on Chinese, (track-specific) mathematics, and English, a basic-skill test, and a comprehensive test: students in the General Science track took the comprehensive test on physics, chemistry, and biology combined and students in the Liberal Arts track took the comprehensive test on history, politics, and geography combined. The total available points are 750 for both tracks: 150 for Chinese, 150 for mathematics, 150 for English, 60 for the basic-skill test, and 240 for the comprehensive test. Each August, the Institute admits students solely based on their total scores in these five subjects. Only students who applied to the Institute and earned a total CET score higher than the admission threshold will be admitted; for example, in 2012, the admission threshold was 573 for the Liberal Arts track and 582 for the General Science track. In the past decade, the mean CET scores of admitted students were close to the 85th percentile of the provincial CET score distribution.

For the purpose of the present study, a particularly helpful feature of the Institute is that dorm room assignments for incoming students are done before enrollment and thus not subject to students' or their parents' preferences. All incoming students admitted in a particular major are randomly divided into two to three administrative classes. Each student is then assigned to a dorm room with five other same-sex first-year students (usually) in the same administrative class. As such, conditional on one's administrative class assignment, roommate assignments are effectively random; this feature is exploited to identify academic peer effects.

2.3. Data and sample characteristics

We collected information on the entire cohort of 290 students entering the Yantai Institute in the fall from administration records provided by the Institute's managerial staff. The data collected include students' major, dorm room number, (raw) scores of all courses taken in fall and spring, CET scores, and demographic characteristics. After excluding six students with missing CET scores information, the analytical sample has 284 valid observations.

Table 1 presents summary statistics of all variables used in the analysis. Nearly two-thirds of the students are female; only 1% of all students belong to ethnic minority groups. Concerning the distribution of majors, more than 60% of the students major in social sciences (Marketing and Public Administration); the rest major in agriculture-related majors (Aquaculture and Facility Agriculture). Such a distribution reflects the relative popularity of social-science majors over agriculture-related majors in China today.

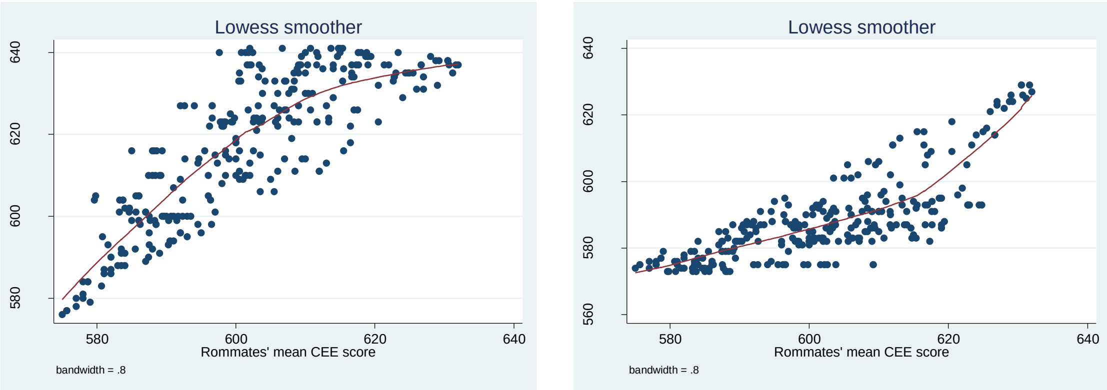
2.4. Variables

The outcome variables of interest are students' overall GPA and GPA measures constructed separately for different course types and semesters. Since required and elective courses differ greatly across majors, we did not further disaggregate students' GPAs down to the course level to retain comparability. The distributions of these GPA measures reveal two informative patterns. First, all these measures have fairly large variations, which helps to detect potential peer effects. Second, elective courses appear to be easier than required ones. GPAs for the former have higher means and smaller standard deviations (SD) than those for the latter in both semesters, suggesting more room for peer interaction in required courses than in elective ones.

The most important explanatory variables are roommates' CET scores, with various definitions. For the purpose of this paper, we constructed three CET variables: roommates' average CET score (CET_{-i}^{M}), the highest-scoring roommate's CET score (CET_{-i}^{H}), and the lowest-scoring roommate's CET score (CET_{-i}^{L}). While these three CET measures are positively correlated, the scatter plots in Figure 1 reveal that both the highest- and lowest-scoring roommates' CET scores capture substantial variations (i.e., those in the vertical direction) that are not captured by roommates' average CET score (that varies in the horizontal direction).

Table 1. Variable definitions and summary statistics (N=284)

Variable	Definition	Mean	Std. Dev.	Min.	Max.
Outcome variables					
$GPA_{overall}$	Overall GPA	2.80	0.63	0.22	3.93
$GPA_{req,F2012}$	GPA for required courses taken in fall 2012	2.76	0.77	0.14	4.0
$GPA_{req,S2013}$	GPA for required courses taken in spring 2013	2.59	0.73	0.31	3.87
$GPA_{elec,F2012}$	GPA for elective courses taken in fall 2012	3.26	0.54	0	4.0
$GPA_{elec,S2013}$	GPA for elective courses taken in spring 2013	3.38	0.58	0	4.0
Explanatory variables					
CET_i	Student *i*'s own CET score	601	19.86	573	641
CET_{-i}^{M}	Roommates' average CET score	601	13.83	575	632
CET_{-i}^{H}	Highest CET-scoring roommate's CET score	618	17.53	576	641
CET_{-i}^{L}	Lowest CET-scoring roommate's CET score	588	12.77	573	629
Female	Dummy, =1 if female, = 0 otherwise	0.61	0.49	0	1
Ethnic minority	Dummy, =1 if ethnic minority, = 0 otherwise	0.01	0.08	0	1
Major					
Aquaculture	Dummy, =1 if aquaculture major, = 0 otherwise	0.17	0.37	0	1
Facility agriculture	Dummy, =1 if facility agriculture major, = 0 otherwise	0.23	0.42	0	1
Marketing	Dummy, =1 if marketing major, = 0 otherwise	0.32	0.47	0	1
Public administration	Dummy, =1 if public administration major, = 0 otherwise	0.29	0.45	0	1



(a) (b)

Figure 1. Highest- and lowest- CET score for (a) highest-scoring roommate's CET score against roommates' mean CET score and (b) lowest-scoring roommate's CET score against roommates' mean CET

2.5. Estimation framework

The linear-in-mean specification commonly adopted in the previous literatures [5], [11]–[23] provide a useful starting point for developing our empirical models, in (1):

$$GPA_i = \alpha + \beta_{own} CET_i + \beta_{peer} CET_{-i}^{M} + \boldsymbol{X}_i \boldsymbol{\delta} + \varepsilon_i. \quad (1)$$

Where, GPA_i is student *i*'s overall GPA; CET_i is student *i*'s own CET score; CET_{-i}^{M} is the average CET score of student *i*'s roommates, defined as $CET_{-i}^{M} = \sum_{j \neq i} CET_i / (N-1)$, where N is the number of students sharing a dorm room at the Institute; X_i is a set of personal characteristics for *i*, including gender, ethnicity, major, and administrative class; the error term ε captures the influence of unobservable factors. For ease of interpretation, student *i*'s GPA, own and roommates' CET scores are standardized to have mean zero and unit SD.

Note that conditional random roommate assignments in our case imply that the conditioning on one's major (or administrative class within majors) effectively addresses both self-selection and omitted-variable problems. In addition, the availability of a pre-college peer-ability measure (CET_{-i}^{M}), which is unlikely to be affected by student *i*'s GPA in college, addresses the reverse-causality problem. In this setup, to the extent that CET_{-i}^{M} is a reasonable measure of peer ability, the parameter β_{peer} captures the *causal* effect of roommates' (pre-college) academic ability and can be estimated using ordinary least-squares (OLS) techniques.

However, two possibilities may render the linear-in-mean framework (1) inadequate for detecting potential peer effects. First, all roommates do not affect a given student equally. For example, while all abler roommates may potentially help improve a given student's academic performance through peer interaction, the academically strongest roommate may also serve as a role model for this student. Thus, the strongest roommate is likely to supply more peer influence than other able roommates. This possibility suggests that roommates' average CET score (CET_{-i}^{M}), an aggregate measure of peer ability, may fail to capture the impact of the most influential roommate.

To examine how different roommates' CET scores might affect the estimates of peer effects, we replace roommates' average CET score (CET_{-i}^{M}) in (1) with roommates' highest CET score (CET_{-i}^{H}) and lowest CET score (CET_{-i}^{L}), respectively, in (2) and (3):

$$GPA_i = \alpha + \beta_{own}CET_i + \beta_{peer}CET_{-i}^{H} + \boldsymbol{X}_i\boldsymbol{\delta} + \varepsilon_i, \quad (2)$$

$$GPA_i = \alpha + \beta_{own}CET_i + \beta_{peer}CET_{-i}^{L} + \boldsymbol{X}_i\boldsymbol{\delta} + \varepsilon_i. \quad (3)$$

Comparisons of results of estimating Equations (1)-(3) allow us to see how the estimate of the peer-effect parameter, β_{peer}, varies with different peer-ability measures. We also include all three measures, CET_{-i}^{M}, CET_{-i}^{H}, and CET_{-i}^{L}, in the same model and test their relative performance on capturing the "true" peer influence.

The second possibility is that even the most influential peer may affect a given student differently in different contexts. For example, one might expect students to have a smaller demand for peer interaction in elective courses than in required ones since the latter tend to be more demanding than the former. Moreover, roommates usually take required courses together (thus becoming classmates in those courses), but they might take different elective courses (which reduces their chance of being classmates in those courses). Hence, the supply of peer interaction may be higher in required courses than in elective courses.

To see how the impact of peer influence differs across contexts, we disaggregate student *i*'s overall GPA in (1) into *k* more disaggregated GPA measures, including those constructed for different types of courses (required versus elective courses) and semesters (fall versus spring):

$$GPA_{i1} = \alpha + \beta_{own,1}CET_i + \beta_{peer,1}CET_{-i}^{M} + \boldsymbol{X}_i\boldsymbol{\delta} + \varepsilon_{i1},$$

$$GPA_{i2} = \alpha + \beta_{own,2}CET_i + \beta_{peer,2}CET_{-i}^{M} + \boldsymbol{X}_i\boldsymbol{\delta} + \varepsilon_{i2},$$

$$GPA_{ik} = \alpha + \beta_{own,k}CET_i + \beta_{peer,k}CET_{-i}^{M} + \boldsymbol{X}_i\boldsymbol{\delta} + \varepsilon_{ik}. \quad (4)$$

While the parameters in the system of (4), $\beta_{peer,k}$, can be estimated equation-by-equation, we jointly estimate all parameters in the *k* equations using Zellner's [28] Seemingly Unrelated Regression (SUR) method, which facilitates cross-equation tests to examine (some of) the following hypotheses:

H_1: Academic peer effects vary with different peer-ability measures used (i.e., $\beta_{peer,\,CET^M} \neq \beta_{peer,\,CET^H}; \beta_{peer,\,CET^M} \neq \beta_{peer,\,CET^L}$).

H_2: Effects of roommates' academic ability are larger in required courses than in elective courses (i.e., $\beta_{peer,req} > \beta_{peer,elec}$).

H_3: Effects of roommates' academic ability decline over time (i.e., $\beta_{peer,F2012} > \beta_{peer,S2013}$).

3. RESULTS AND DISCUSSION

3.1. Conditional random roommate assignment

All analyses reported and discussed were performed in STATA 14. Before discussing the main results of this paper, it is helpful to present evidence supporting the key identification assumption, i.e., random roommate assignments (conditional on one's major/administrative class). Table 2 reports the results. Column 1 indicates that, before controlling for major or administrative class effects, roommates' average CET score is strongly correlated with one's own CET score (coefficient=0.51, p=0.000). Yet when conditional on major fixed effects (column 2) and further on administrative-class fixed effects (column 3), the coefficient of roommates' average CET score becomes essentially zero; further including students' personal characteristics in column 4 leads to a negligible change in the estimate. Finally, columns 5 and 6 re-estimate the model in column 4 but replace roommates' average CET score with roommates' highest and lowest CET scores, respectively, in the model. Neither of these two peer-ability measures is significantly correlated with one's own CET score. These results lend strong support to the presumption of (conditional) random roommate assignments. Since administrative classes are proper subsets of majors in the Yantai Institute, we control for administrative-class fixed effects in all regressions.

Table 2. Partial correlations between one's own and roommates' CET scores

Variable	Outcome variable=One's *own* CET Score (standardized)					
	(1)	(2)	(3)	(4)	(5)	(6)
Roommates' mean CET score	0.510***	0.069	0.046	0.024		
(standardized)	(0.081)	(0.145)	(0.154)	(0.168)		
Roommates' highest CET score					-0.076	
(standardized)					(0.130)	
Roommates' lowest CET score						0.040
(standardized)						(0.155)
Female				3.180	2.806	2.958
				(2.315)	(2.265)	(2.619)
Ethnic minority				-10.141*	-9.320*	-10.023*
				(5.807)	(5.554)	(5.480)
Major fixed effects	No	Yes	Yes	Yes	Yes	Yes
Administrative-class fixed effects	No	No	Yes	Yes	Yes	Yes
N	284	284	284	284	284	284
R^2	0.125	0.232	0.238	0.246	0.247	0.246

Notes: Coefficients in columns 1-6 are estimated by OLS. All regressions include a constant term; Standard errors are reported in parentheses, adjusted for within-dorm room clustering; *Significant at 10% level; *** Significant at 1% level.

3.2. Which roommate matters?

Column 1 of Table 3 reports the estimated effect of roommates' (pre-college) academic ability, based on the conventional linear-in-mean specification of (1). It suggests that a one-SD increase in (randomly assigned) roommates' average CET score leads to a 0.147-SD increase in one's overall GPA, an impact that is only marginally significant. The lack of statistical significance may be due to the small size of our sample, but it is also possible that the peer-ability measure used, i.e., roommates' average CET score, contains too much noise, thus failing to capture the impact of the most influential roommate. Since roommates are (conditionally) randomly assigned, the errors contained in roommates' mean CEE score are presumably random noises, which would lead to an attenuation bias [29]–[31], pushing the estimated peer effect toward zero.

Table 3. Impacts of roommates' highest/mean/lowest CET score on individual students' overall GPA

Variables	Outcome variable=One's own overall GPA (standardized)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Own CET score (standardized)	0.440***	0.448***	0.442***	0.451***	0.432	0.438***	0.461***
	(0.069)	(0.065)	(0.069)	(0.063)	(0.432)	(0.067)	(0.068)
Roommates' CET score (standardized)							
Mean score	0.147*			-0.127			
	(0.085)			(0.179)			
Highest score		0.267***		0.360**	0.267***	0.267***	0.269***
		(0.094)		(0.146)	(0.094)	(0.093)	(0.094)
Lowest score			0.036	0.030			
			(0.071)	(0.114)			
Classmates' CET score (standardized)							
Mean score					-0.212		
					(5.328)		
Highest score						-0.464	
						(0.541)	
Lowest score							0.290
							(0.318)
Female	0.336**	0.448***	0.341**	0.485***	0.448***	0.448***	0.452***
	(0.134)	(0.140)	(0.137)	(0.142)	(0.141)	(0.140)	(0.141)
Ethnic minority	0.358	0.351	0.453	0.394	0.350	0.359	0.362
	(0.532)	(0.481)	(0.586)	(0.483)	(0.483)	(0.481)	(0.484)
Administrative class fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	284	284	284	284	284	284	284
R^2	0.268	0.286	0.259	0.288	0.286	0.287	0.287

Notes: Coefficients in columns 1-4 are estimated by OLS. All regressions include a constant term; Standard errors are reported in parentheses, adjusted for within-dorm room clustering; *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

To explore which roommate's CET score matters the most, columns 2 and 3 of Table 3 replace roommates' average CET score with their highest and lowest CET scores, respectively, in the model. The results reveal that it is the highest-scoring roommate's CET score that drives the estimated peer effect reported in column 1. More specifically, a one-SD increase in the highest-scoring roommate's CET score raises one's overall GPA by 0.267 SDs (Table 3, column 2), almost twice the impact of roommates' average CET score (column 1). In contrast, the lowest-scoring roommate's CET score has virtually no impact on one's overall GPA (column 3). To further assess the relative performance of the three peer-ability measures, column 4 of Table 3 includes all three CET scores in the model. Again, while the highest-scoring roommate's CET score has a significant impact on one's overall GPA, the other two have little impact. These findings lend strong support to hypothesis H_1, suggesting that, at least in our focal college, only the highest-achieving roommate's ability matters in peer interaction among roommates.

Further checking the potential concern that the roommate effect found in column 2 actually picks up the effect of classmates' academic ability, we added classmates' highest, mean, and lowest CET scores, along with roommates' highest CET score, respectively, in columns 5, 6, and 7. The results show that while the effect of roommates' highest CET score remains unchanged, the effects of classmates' CET scores are all statistically insignificant, suggesting that the highest-scoring roommate's academic ability is indeed the driver of peer effects in the focal college. Therefore, in what follows, we use the highest-scoring roommate's CET score as the key explanatory variable.

3.3. Peer effect on what?

Two informative patterns are further revealed when students' overall GPA is disaggregated by course type and semester in Table 4. First, in support of hypothesis H_2 discussed, the estimated peer effect is, in general, greater in required courses than in elective courses in both semesters. For both fall and spring, the impacts of the highest-scoring roommate's CET score on one's required-course GPA (columns 1, 2) are larger than those on one's elective-course GPA (columns 3, 4), although the differences are not statistically significant. Second, in support of hypothesis H_3, the estimated peer effect declines over time for both required and elective courses. Most strikingly, moving from fall (Table 4, column 1: $\hat{\beta}_{peer,req,F2012}$=0.322) to spring (Table 4, column 2: $\hat{\beta}_{peer,elec,S2013}$=0.186), the impact of roommates' highest CET score in required courses declines by more than 40%, a drop that is significant at the 2% level. As one would expect, the greatest contrast (size wise) comes from the comparison between peer effects on one's required-course GPA in fall 2012 (column 1: $\hat{\beta}_{peer,req,F2012}$=0.322) and one's elective-course GPA in spring (column 4: $\hat{\beta}_{peer,elec,S2013}$=0.140), which is significant at the 8% level. These patterns suggest that assessing academic peer effects using aggregated GPA measures may mask some important driving channels. Had those previous studies that did not find significant peer effects [9], [15], [16] exploited more disaggregated outcome measures, they might have discovered academic peer effects that are larger and more statistically significant than what they have found.

Table 4. Impacts of the CEE score of the highest-scoring roommate

Outcome variables	Required courses GPA (standardized)		Elective courses GPA (standardized)	
	(1)	(2)	(3)	(4)
	Fall 2012	Spring 2013	Fall 2012	Spring 2013
Own CET score	0.428***	0.481***	0.198***	0.116*
(standardized)	(0.058)	(0.057)	(0.058)	(0.066)
Highest-scoring roommate's CET score	0.322***	0.186**	0.285***	0.140
(standardized)	(0.080)	(0.079)	(0.080)	(0.090)
Constant/Covariates	yes	yes	yes	yes
Administrative class fixed effects	yes	yes	yes	yes
N	284	284	284	284
R^2	0.286	0.302	0.276	0.083

Notes: Coefficients in columns 1-4 are jointly estimated by SUR; All regressions include a constant term and dummies for female and ethnic minorities; Standard errors are reported in parentheses, adjusted for clustering at the dorm room level; *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

While the simple demand-and-supply framework provides some useful guidance for predicting the patterns found before, such guidance seems to be too broad. More detailed driving channels may be uncovered to understand academic peer effects among college students better. For example, the smaller peer effect found in elective courses is likely due to students' lack of effort devoted to studying and seeking peer assistance in taking these courses, which are less demanding and less critical for students' careers than are required courses. In support of this explanation, the coefficient of one's own CET score, which captures, at least partly, the impacts of one's motivation and effort, is significantly smaller in elective courses than in required courses for both semesters ($\hat{\beta}_{own,req,F2012} - \hat{\beta}_{own,elec,F2012}$=0.23, p=0.0001, $\hat{\beta}_{own,req,S2013} - \hat{\beta}_{own,elec,S2013}$=0.365, p=0.0000). Note, however, that the lack-of-effort hypothesis *alone* cannot fully explain the significant decline in the size of peer effects over time in *required* courses ($\hat{\beta}_{peer,req,S2013} - \hat{\beta}_{peer,req,F2012}$=−0.136, p=0.0159). If students devote less effort to learning in required courses over time, one would expect a decline in the coefficient of one's own CET score in required courses. Yet, the own-CET coefficient in required courses increases slightly over time, although not in a statistically significant manner ($\hat{\beta}_{own,req,S2013} - \hat{\beta}_{own,req,F2012}$=0.053, p=0.2049), which does not seem to support the lack-of-effort hypothesis. Alternatively, the difference in the temporal patterns of the own- and roommate-CET impacts suggests that students tend to substitute their own ability for peer ability in taking required courses, as they become academically more independent over time, even though they may devote less effort to learning over time. Unfortunately, due to data limitations, we are unable to follow these students over time to test whether this fading pattern continues as they spend more years in college.

3.4. Peer effects for whom?

Besides presenting informative patterns of academic peer effects, Table 3 also reveals a significant *gender* difference in academic performance in the sample. All else equal, female students outperformed male students by more than 0.3 SDs of the overall GPA. There may also be heterogeneity in peer effects across fields of study and students' ability levels since the administrative-class (major) fixed effects (—detailed results on fixed effects are not shown but available upon request) and one's own CET score are all statistically significant (p=0.000) in models presented in Table 3.

Table 5 thus examines potential heterogeneity in academic peer effects across gender groups (Panel A), fields of study (Panel B), and individual students' ability levels, measured as their position (above- or below-median) in the own-CET score distribution (Panel C). Estimated coefficients of one's own CET score are also presented for comparison. A general observation is that for all six subgroups considered in the table, the patterns of the own CET-score effect mirror closely those previously discussed, i.e., own CET-score effects are higher in required courses and increase over time in both required and elective courses. Table 5 also reveals apparent heterogeneity in peer effects across different subgroups, which are worth exploring to gain more insights into the formation of academic peer effects.

First, male students respond more strongly to (the highest-scoring) roommates' academic ability than female students in all cases examined (Panel A). This finding suggests that compared with female students, male students are more likely to be "group learners," or they admire their highest-scoring roommates more, or both. Note that this finding is at odds with what Han and Li [17] found in another Chinese college. The discrepancy in the role gender plays in driving academic peer effects in different colleges no doubt calls for more research. Second, consistent with the findings of Brunello *et al*. [14], larger peer effects of (the highest-scoring) roommates' ability are found among students majoring in relatively "harder" sciences (agriculture-related majors in our case), compared with those found among social-science majors (Panel B). Third, significant peer effects exist among students with above-median ability in required courses but not those with lower ability levels (panel C). Since above-median students presumably demand less help from their peers than their below-median counterparts, the larger peer effects found among the former are likely due to their higher motivation to learn. Consistent with this interpretation, significant peer effects are also found in elective courses (taken in fall) among above-median students. Finally, the two patterns discovered in Table 3 are seen again in Table 5. In virtually all sub-panels, peer effects are largest for required courses taken in fall, while own-CET impacts are largest for those taken in spring, which again suggests that students substitute their own ability for peer ability over time.

Despite the relatively small size of our sample, our analysis found significant peer effects on students' academic performance. Three important findings, all consistent with the supply-and-demand interpretation previously proposed, emerged when disaggregated measures were used in the analysis. First, it is the academic ability of the highest CET-scoring roommate, who is presumably the most effective supplier of peer effects. Conditional on roommates' highest CET score, which has a significantly positive effect on one's GPA, roommates' average and lowest CET scores have essentially no impact. This finding suggests that the commonly-adopted linear-in-mean specification may fail to discover the influence of the most influential peer. Second, peer effects are larger on one's performance in required courses than in elective ones. Arguably, required courses tend to be more technical than elective ones, demanding more analytical skills and creating more demand for peer interaction among students. Finally, whereas peer effects decline over time for both types of courses, the effects of one's own CET score increase over time. This finding suggests that students tend to substitute their own ability for peer ability as they become academically more independent.

Table 5. Estimated effects of own and highest-scoring roommates' CET scores

Outcome variables	(1) Overall GPA (standardized)	(2) Required courses GPA (standardized) F2012	(3) Required courses GPA (standardized) S2013	(4) Elective courses GPA (standardized) F2012	(5) Elective courses GPA (standardized) S2013	(6) *N*
Male						
Own CET score (standardized)	0.434***	0.370***	0.539***	0.099	0.079	
	(0.096)	(0.101)	(0.092)	(0.098)	(0.099)	112
Highest roommate CET score (standardized)	0.424*	0.456**	0.402*	0.396*	0.280	
	(0.221)	(0.232)	(0.212)	(0.225)	(0.228)	
Female						
Own CET score	0.519***	0.505***	0.513***	0.333***	0.194**	
	(0.071)	(0.070)	(0.071)	(0.071)	(0.089)	172
Highest roommate CET score (standardized)	0.295***	0.319***	0.219***	0.299***	0.144	
	(0.084)	(0.083)	(0.084)	(0.084)	(0.105)	
Agriculture related						
Own CET score (standardized)	0.325***	0.295***	0.383***	0.045	0.047	
	(0.084)	(0.083)	(0.083)	(0.069)	(0.074)	114
Highest roommate CET score (standardized)	0.301*	0.384**	0.246	0.206	-0.093	
	(0.155)	(0.152)	(0.153)	(0.128)	(0.137)	
Social sciences						
Own CET score (standardized)	0.563***	0.556***	0.572***	0.346***	0.152	
	(0.077)	(0.077)	(0.077)	(0.089)	(0.104)	170
Highest roommate CET score (standardized)	0.227***	0.267***	0.139	0.291***	0.219*	
	(0.087)	(0.087)	(0.087)	(0.101)	(0.117)	
Below median						
Own CET score (standardized)	0.597**	0.490**	0.649***	0.508**	0.126	
	(0.234)	(0.246)	(0.240)	(0.253)	(0.297)	144
Highest roommate CET score (standardized)	0.159	0.182	0.111	0.190	0.186	
	(0.118)	(0.124)	(0.120)	(0.127)	(0.149)	
Above median						
Own CET score (standardized)	0.389***	0.372***	0.428***	-0.002	0.099	
	(0.122)	(0.113)	(0.119)	(0.108)	(0.121)	140
Highest roommate CET score (standardized)	0.338***	0.404***	0.248**	0.330***	0.087	
	(0.105)	(0.097)	(0.102)	(0.092)	(0.104)	

Notes: Coefficients in columns (1)-(5) in each panel are jointly estimated by SUR. Standard errors are reported in parentheses, adjusted for clustering at the dorm room level; *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level.

4. CONCLUSION

As the simple demand-and-supply framework predicts, the level of data aggregation matters for identifying academic peer effects among college students. Firstly, the conventional linear-in-mean specification commonly adopted in the literature may fail to capture the influence of the most influential peer. Although linear-in-mean models reveal a (marginally) significant impact roommates' average ability has on individual students' overall GPA, it is the highest-achieving roommate's ability that drives this impact.

Second, as an outcome measure, students' overall GPA masks important driving channels of academic peer effects. More informative patterns were recovered when more disaggregated GPA measures were used in estimation. In general, peer effects are larger and more significant in required courses than in elective courses, suggesting that students have a higher demand for peer interaction in taking (the relatively more demanding) required courses. Yet even when taking required courses, students tend to substitute their own ability for peer ability as they become more academically independent over time. Most importantly, despite the existence of heterogeneity of peer effects found across gender groups, ability levels, and academic fields, the substitution patterns persist in all subgroups we analyzed. In particular, peer effects are the highest in required courses taken in the first semester. Therefore, while heterogeneity in peer effects adds a layer of complexity to the issue of how to organize student groups efficiently, it is clear from our findings that college administrators should exploit peer effects to improve student performance as early as possible.

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